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Advanced Motion Control of Four In-wheel Motor Actuated Vehicles*

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***Abstract*— Advanced motion controllers combining model-based and model-free methods are proposed to solve two problems of the benchmark challenge organized by IEEE CDC 2023. The proposed controllers allow the vehicle to track the target speed and trajectory while effectively suppressing its vertical acceleration on rough roads. First, the vehicle dynamics model is established, and its unknown parameters are identified via the nonlinear least squares method. Second, a longitudinal motion controller is proposed based on nonlinear control methods to track the target speed. Finally, the vehicle states, including vertical acceleration, body roll angle, and body pitch angle, are suppressed by torque allocation based on model-free reinforcement learning. Co-simulations of Modelon Impact and MATLAB/Simulink have been performed, and the results show that our methods are initially effective and promising.**

I. Introduction

Automation and electrification are two important trends in the development of the automotive industry. Vehicle motion control is the basis for the realization of autonomous driving technologies. Although this problem has been addressed in the field of vehicle engineering in the past decades, it has not attracted much attention in the academic field of control and decision-making. Therefore, the study of motion control of four in-wheel motor-actuated vehicles is meaningful and important. Two problems of the benchmark challenge organized by IEEE CDC 2023 are as follows:

- Problem 1: For the problem of acceleration and braking on rough wet straight roads, we should not only track the target speed but also consider the vehicle states and body angles with the minimum energy consumption.
- Problem 2: For the ISO two-lane transformation problem on rough and uneven roads: we must not only track the desired route to the maximum extent but also control the driving state and body posture of the vehicle with the minimum energy consumption.

The control strategies of longitudinal motion mainly include model-based optimal control, neural network control,

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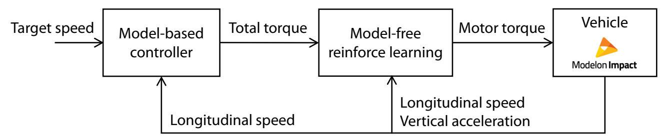

Fig. 1. The diagram of the proposed control strategy.

and fuzzy control. The above methods can realize the accurate tracking of longitudinal speed when the vehicle parameters are known. However, they have not yet considered whether the tracking of longitudinal speed is effective when the vehicle model is unknown. There are also lots of studies focusing on vehicle lateral-longitudinal-vertical motion control. F. Xiao et al. [1] studied the three-dimensional stability region and proposed an integrated control framework of active front-wheel steering, active suspension, and direct yaw moment control. J. Zhao et al. [2] proposed a new integrated controller with a three-layer recursive structure to coordinate the three interactions. S. Zhao et al. [3] proposed a multilevel recursive order control theory realizing the function decoupling of the vehicle chassis system.

Reinforcement learning is the branch of machine learning that emphasizes exploring actions and learning based on the environment to maximize expected benefits. The basic principle of reinforcement learning is to learn the optimal strategy to maximize the cumulative rewards of the intelligent body through trial and error, constant interaction with the environment, and constant revision of the intelligent body's strategy, which ultimately maximizes the rewards or achieves the specified goal. Q-learning algorithm is a typical value-based reinforcement learning algorithm, which has the advantages of fewer required parameters, no need for environment modeling, and can be implemented offline, and is one of the most effective algorithms currently applied to four-wheel drive vehicle path planning.

II. Methods

The diagram of the proposed control strategy is shown in Fig. 1. Firstly, a model-based control strategy based on the longitudinal model is adopted to obtain the total torque demand. The unknown parameters of the longitudinal model are identified by using the nonlinear least squares method. Then, reinforcement learning is used to allocate the total required torque to reduce energy consumption and suppress vertical acceleration.

The details of the model-based control strategy are to identify the vehicle's longitudinal model and obtain the total torque demand of the vehicle. The longitudinal motion controller is designed within the framework of the output feedback nonlinear control method. The specific method

Algorithm 1 Q-learning Algorithm

Initialize $Q(s,a)$ with zeros, initialize R_j with zero
for $i = 1 : N$ **do**
  Initialize s
  for $j = 1 : M$ **do**
    Choose action a_j, observe R_j, s_{j+1} from environment
    Updating the Q-table: $Q(s_j, a_j) \leftarrow Q(s_j, a_j) + c\left[R_j + r * \max\left(Q(s_{j+1}, a_j)\right) - Q(s_j, a_j)\right]$
  end for
end for

of reinforcement learning is to use the Q-learning method, which uses the constraints of vertical acceleration and energy consumption as the reward function. The specific algorithm process is shown in Algorithm 1, where c is step size, r is the discount factor, s is the state of the vehicle, a is the distributed torque, and R is the reward.

The reward R can be calculated as

$$R = jv3 + pena, \tag{1}$$

$$pena = \begin{cases} -1000, & |a_z| > 0.4, |\phi| > 0.014, |\theta| > 0.005 \\ 0, & \text{others}, \end{cases} \tag{2}$$

where $jv3$ is energy consumption, $pena$ is the penalty for exceeding constraints, a_z is vertical acceleration, ϕ is the pitch angle, θ is the roll angle. Decision-making is performed by constructing a Q-table, where each element of the Q-table measures the maximum expected cumulative payoff that will be obtained when a given action is taken in a given state. Therefore, the intelligent body can select the optimal action in each state according to the Q-table. Based on vehicle dynamics, it is known that changes in vehicle road conditions are coupled to the vehicle through vertical load, so in this paper, the vertical acceleration is used as the state quantity in Q-learning, and the body attitude-pitch, side inclination, and front/rear axle allocation ratio are used as the reward function to train the appropriate allocation strategy to control the body attitude as well as the vehicle stability.

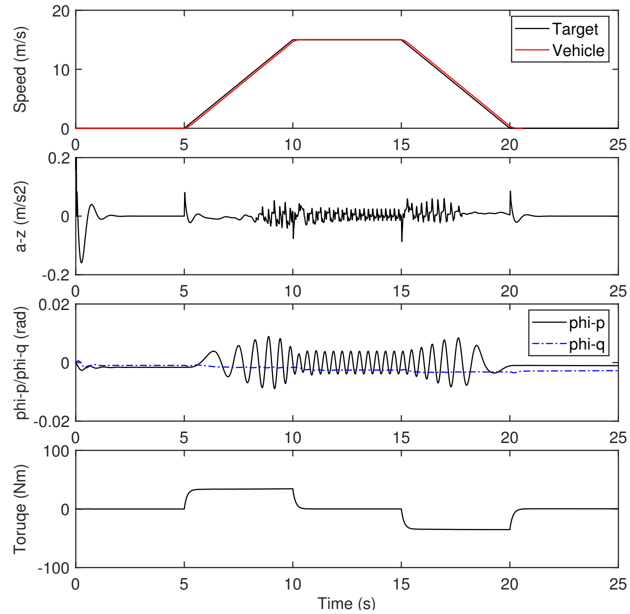

Fig. 2. Co-simulation results of Problem 1.

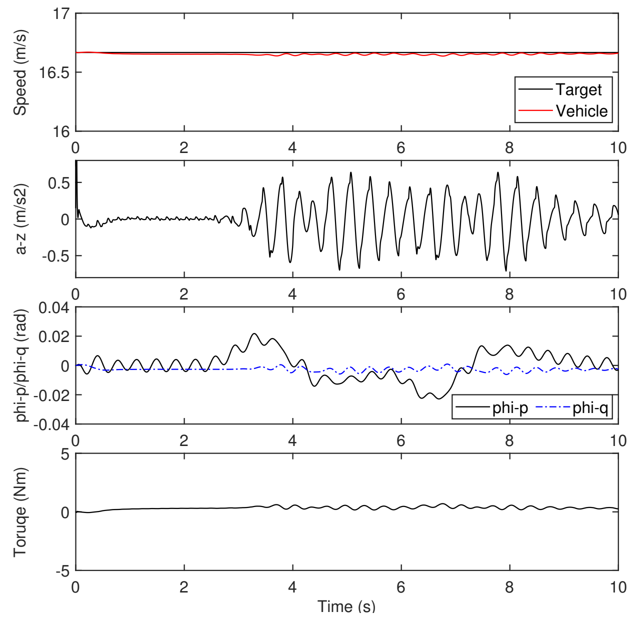

Fig. 3. Co-simulation results of Problem 2.

III. Results

The preliminary results of our work are given based on co-simulations of Modelon Impact and MATLAB/Simulink, as shown in Figs. 2 and 3. It should be noted that these preliminary results are obtained with the basic PID controller, not the methods mentioned in Section II. We are developing more advanced controllers described in Section II, and new results will be given by the poster at the end of November. Co-simulation results show that the longitudinal speed can track the target speed, and the vertical acceleration is within its constraint range. In addition, the pitch angle and roll angle are also below constraints, satisfying the requirements.

IV. Conclusions

The research content of this paper is to design vehicle motion controllers for state suppression, energy conversation, and the tracking of speed and trajectory of four in-wheel actuated vehicles. The proposed methods will be developed further until the beginning of the Autonomous Driving Control Benchmark Challenge of IEEE CDC 2023.

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